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A short Reflection on the Strengths and Weaknesses of Simulation Optimization

P. Vazan, P. Tanuska

Abstract**—**The paper provides the basic overview of simulation optimization. The procedure of its practical using is demonstrated on the real example in simulator Witness. The simulation optimization is presented as a good tool for solving many problems in real praxis especially in production systems. The authors also characterize their own experiences and they mention the strengths and weakness of simulation optimization.

Keywords**—**discrete event simulation, simulation optimization, Witness

I. INTRODUCTION

SIMULATION optimization is the most significant simulation technology in the last years according to many authors. It eliminates one of disadvantages of simulation and it is used to find the best solution from many simulation experiments.

We can already observe the rapid development of simulation optimization for several years. The combination simulation and optimization has already been expected for a long time, but only in the last decade it has achieved real development. Of course the increasing power of computers has helped with the progress of simulation optimization, but the over-riding factor that has turned things around for simulation optimization is the remarkable research that has taken place in various areas of computational operations research — research that has either given birth to new optimization techniques that are more compatible with simulation, or in many cases research that has generated modified versions of old optimization techniques that can be combined more elegantly with simulation.

Today, leading simulation software vendors have introduced optimizers that are fully integrated into their simulation packages. Simulation practitioners now have access to robust optimization algorithms and they are using them to solve a variety of “real world” simulation optimization problems [2].

There also exist many barriers which have to be over-came for broader simulation optimization using. Great scepticism predominates to the results of simulation optimization in concrete applications.

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II. SIMULATION OPTIMIZATION

A. Definition

The definition of simulation optimization is very easy. We introduce one of the definitions of simulation optimization: Simulation optimization is defined as optimization of outputs from simulation experiments. It is based especially on optimization of outputs from discrete event simulation models [5]. A lot of analysts and engineers doubt that simulation optimization is a real optimization technique.

Let’s do a short comparison of classic optimization and simulation optimization. Most of the optimizing methods use descriptive model. They are covered in operational research. This model can be written as a function:

$$Y=f(x_1,x_2,...,x_n), \quad (1)$$

where $Y=(y_1,y_2,...,y_m)$

It means that the value of output variable Y is a function ofcombinations ofvaluesof inputvariables-independentvariables x_i. The function f is a mathematical function and it is possible to calculate the value of output variable Y or y_i. To be considered as an optimization model(1), the modelhas to beinvolved into the model the goal of optimization e.g.

$$Y=f(x_1,x_2,...,x_n) = \text{minimum} \quad (2)$$

also into conditions and constrains for limitation of input variables. Formula (1) is called the objective function. The optimal solution is searched by the analytic solution, it means by calculation [6].

It is possible to define the simulation model as a function

$$Y=f(p_1,p_2,...,p_n), \quad (3)$$

where $p_i$are input parameters.

Y is output variable that is obtained as output from simulation model through simulation experiment. Similarly the simulation model can be used for finding the optimal solution. In this case the function (3) cannot bewritten asa mathematical function. It means that the values of output variables can be obtained only through the simulation experiment with the simulation model. The defined simulation model cannot be considered as the optimization model because the objective of optimization is not specified. The objective function has to beadded into the simulation model. The objective function is defined:

$$z=g(p_1,p_2,...,p_n, y_1,y_2,...,y_m) \quad (4)$$

Similarly the optimization goal has to be declared:

$$z=g(p_1,p_2,...,p_n, y_1,y_2,...,y_m) = \text{minimum} \quad (5)$$

It is obvious thatall outputvariablesof optimizationsimulation modelarevariablesthe values of which arecalculatedafter thesimulationrun [6]. We hope that this short comparison helps to make the difference between classic and simulation optimization more clear.

Simulation optimization involves two important parts:

1) Generating candidate solutions
2) Evaluation of their objective function value

As it was mentioned above the value of objective function cannot be evaluated directly, but it must be estimated as output from simulation run. It means, that optimization via simulation is computationally very expensive. On the other side the definition of objective function is very simple without complicated mathematical formula.

The goal of optimization is to find maximum or minimum of objective function when different constraints have to be fulfilled.

As in ordinary optimization problem, also the simulation optimization problem is defined by primary components [5]:

1) input and output variables;
2) objective function;
3) Constraints.

Constraints are often welcome in optimization problems as they can significantly reduce the search space, thus accelerating the operation of an algorithm.

The objective function and constraints can involve both the input and output variables, and either (or both) can involve stochastic components. Since the output variables are performance measures of simulation model, they are quantitative in nature. However, unlike standard mathematical programs, the input "variables" may be either quantitative or qualitative. For quantitative input variables, one distinguishes between the continuous values and discrete values, and in the discrete case between a large state space (uncountable, countable infinite, or just combinatorially large) and a relatively small one. In the latter case, the optimization problem is reduced to an exhaustive comparison of candidate solutions, for which ranking and selection methods are particularly suited.

B. The algorithms and software solutions for simulation optimization

Understandably there are a lot of methods that could be used for simulation optimization. The major simulation optimization methods are displayed on fig. 1. However, most developers have involved heuristic search methods into the software packages for simulation optimization. The heuristic search algorithms provide good, reasonably fast results on a wide variety of problems.

We mention at least a few important heuristic algorithms. Here belong genetics algorithms, evolutionary strategies, simulated annealing, simplex search, tabu search (fig. 1) [4,8].

The computationally demands of simulation optimization cause, that the practical usage of simulation optimization is possible without software support. The software packages are solved as plug-in modules which are added in the basic simulation platform. The approach to simulation optimization is based on viewing the simulation model as a black box function evaluator. The optimizer chooses a set of values for the input parameters and uses the responses generated by the simulation model to make decisions regarding the selection of the next trial solution [1].

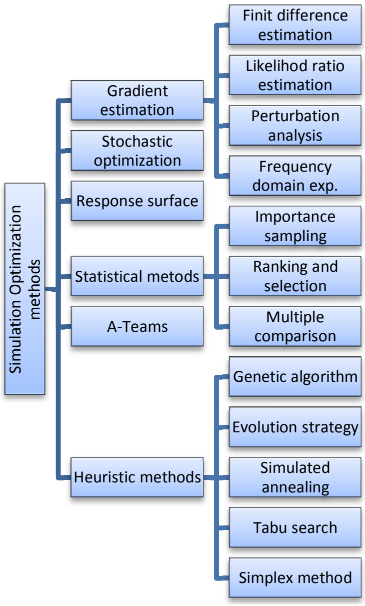

Fig. 1 The important methods of simulation optimization [7]

III. The Realization of Simulation Optimization

We will demonstrate the usage of simulation optimization on the example of the real production system. We will show not only the procedure of realization but we will also emphasize the strengths and weakness of simulation optimization. The example was realized in simulator WITNESS of the British company Lanner Group Ltd. This simulator is oriented mainly for the simulation of production, service and logistic processes. So mainly it supports discrete-event simulation. Generally discrete-event simulation model is defined as one in which the state variables change only at those discrete points in time at which events occur. Discrete event simulation is a very valuable technique for investigating the behavior of many systems [3].

A. General steps of simulation optimization

Simulation optimization typically works in the following way [10]:

1) An initial set of parameter values is chosen and one or more replication experiments is carried out with these values;
2) The results are obtained from the simulation runs and then the optimization module chooses another parameter set to try.
3) The new values are set and the next experiment set is run.
4) Steps 2 and 3 are repeated until either the algorithm is stopped manually or a set of defined finishing conditions are met.

This general procedure seems to be very clear and simple, but its realization is much complicated. The following example shows some important aspects of the realization of simulation optimization in simulator Witness.

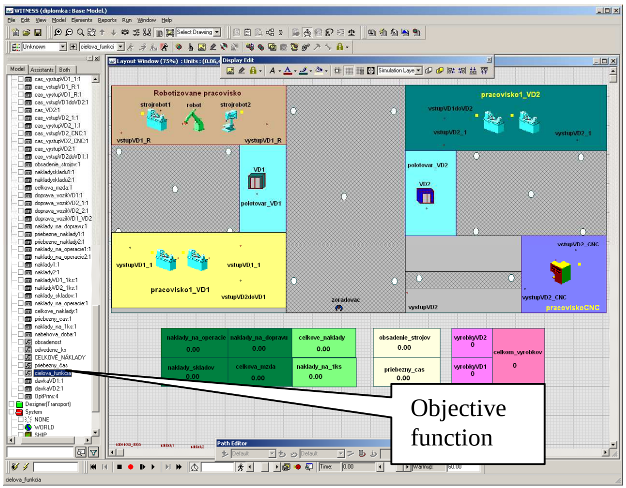

Fig. 1 The simulation model of manufacturing system in Witness

B. The solution

This example demonstrates the process of the searching of optimal values of lot size in the real production system (see fig. 2).The simulation model of the flexible manufacturing system consisted of four machine groups. There were two relative kinds of products named VD1 and VD2 in manufacturing system produced at the same time. The schedule of operations was created for every type of product. The sequence of operations was created for every machine group but the realization of operation on the concrete machine in the group was decided by immediate situation [9].

The basic advantage of simulation optimization is that the objective function can be defined in a simple way and it does not need to contain input values. The objective function is defined insidethe simulation model.

The procedure was defined as follows [9]:

IF No_out_parts () ≥ default value of finished parts AND Machine utilisation ()≥ default value of machine utilisation AND Flow time ()≤ default value of flow time

Unit_Costs = SumCosts / No_out_parts

RETURN Unit_Costs

ELSE

Unit_Costs = SumCosts / No_out_parts

RETURN Unit_Costs

ENDIF

Objective function returns the value of costs per finished part when quantitative values of defined manufacturing goals are fulfilled. At the beginning it is necessary to define default values of flow time, machine utilization and number of finished parts. These values were found out by simulation way from so called preparatory experiments.The existence of correct simulation model is necessary condition of simulation optimization usage. The word “correct” is needed to understand in such a way that the model was validated.

The objective function is defined inside the simulation model in Witness. Typically it will use measures from the simulation such as the number of goods shipped, customer served, staff utilizations and like that [9].

The next step of realization of simulation optimization is realized in plug-in module Optimizer. The fig.3 shows the dialog window of Optimizer. The user chooses the objective function in module Optimizer. It is taken over from simulation model [9].

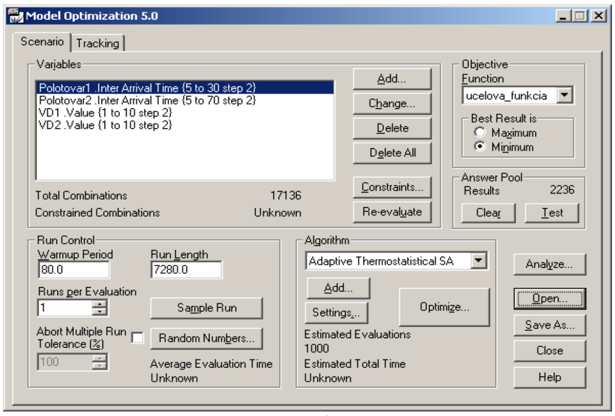

Fig. 3 The dialog window of module Optimizer

The next step is the definition of input variables. The selection of variables that influences the objective function has to follow from knowledge of solved problem and its representation in simulation model. It may be the critical step. It is important to know that the big number of the input parameters and their big range spin out the time of searching of optimal extreme of the objective function. The optimizer for obtaining of one value of objective function has to realize at least one simulation run. For example if the number of possible combinations of input parameters is 100000 and we use All combination algorithm and the retrieval of the value of objective functions lasts 1 second (in complex models it lasts longer), the search of the global extreme of objective function will last more than 27 hours. This is probably unacceptable. Of course, the Optimizer automatically realizes the whole process of the search of global extreme.

There is a question how to eliminate the big range of input parameters. The Optimizer offers several possibilities:

1) To use the appropriate step of the change of input parameters or to define only chosen values.
2) To define constrains with help of functional dependence among input parameters.
3) To choose suitable algorithm for optimization

Understandably the number of input variable and their ranges markedly influence the time of simulation optimization process. We recommend verification of ranges of input variables by specially designed preparatory experiments. The goal of these experiments is very sensitively set up the range of variables so that the total number of possible combinations will be minimal.

The algorithm selection.

Although simulation optimization represents powerful tool, its real usage needs complex knowledge and appropriate procedure. The selection of the proper algorithm is the important part of this procedure.

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The following algorithms for simulation optimization were included for this example.[10]:

1) All combinations – brute force algorithm.The algorithm All combinations always guarantees optimal value finding, but the time of optimum searching is too long and unacceptable in many cases. Usually it is impossible to use this algorithm at the beginning of optimization process.
2) Random solutions – chooses random values from set of variables. It has reached good results when the total number of input values combination was big and the searching step was 1. It is advantageous to use the algorithm Random Solutions at the beginning of optimization process. It offers overview of scanned space. Then it is possible to reduce this space according to the results of the algorithm.
3) Min/Mid/Max – tets only minimal, middle and maximal values of input variables, therefore the number of tested combinations was relatively small. The short searching time was up to the small sample, but the accuracy was low. The efficiency of the algorithm Min/Mid/Max is better for narrow ranges of input variables.
4) Hill Climb – a simple algorithm. Fast but prone to get stuck in local optima.
5) Adaptive Thermostatistical SA – a variant of simulated annealing with extra adaptive nature. Includes some elements of taboo search. Developed by Lanner in conjunction with optimization experts specifically to tackle simulation experimentation. According to our tests was the best in majority of experiments from the point of view of accuracy and the searching time. This algorithm had very good results also at bigger searching step in tests [7]. We recommend usage of Adaptive Thermostatistical Simulated Annealing algorithm if the total number of input values combination is great and also if the searching step is bigger.

The acceleration of the retrieval of global extreme of objective function allows many algorithms. These algorithms need not search all set of possible combinations. Here arises a question if these algorithms will not find only local extreme. It is typical for Hill climbing algorithm.

The selection of algorithm has to respect mainly two basic factors:

1) What data will individual sets of variables include – it concerns if we know all data files of given range or if we only know the minimum, mean and maximum value.
2) Time of optimization process.

C. The next factors which influence simulation optimization

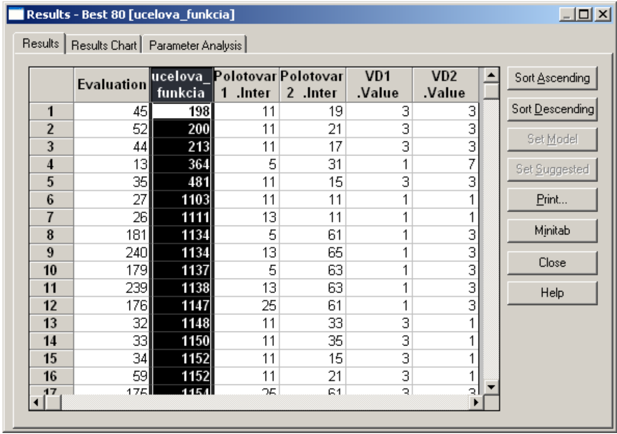
The next factors which influence simulation optimization are:

1) the length of simulation runs. It directly influences the time of simulation optimization realization.
2) the search step. It influences the quality of optimization. The search step should be defined on dependence on the number and ranges of input variables. We suggest set up the search step 2 or 3 for wide range (30 and more values). The bigger step is usually defined for the first optimization experiment. Here exist two criteria for search step determination – the reduction of the number of combination and the reduction of time of optimization. The determination of search step is related to algorithm selection.
3) the number of simulation runs for the objective function evaluation. It directly influences the time of optimization process. The number of simulation runs depends on the character of simulation model. It is necessary to realized more simulation runs when the model is stochastic. Only one simulation run is needed for deterministic model.

The authors recommend the following procedure for algorithm selection and optimisation process realization:

1) Reduce the range of inputs variables by specially designed preparing experiments. The right range represents such states of the system that will be explored. The constraints of inputs variables represent upper and lower limits for system loading in the presented example.
2) Use algorithm Random solutions or Adaptive Thermostatistical SA with bigger step (2 and more).
3) Reduce range of input variables again and repeat experiment by using the Adaptive Thermostatistical SA algorithm.
4) If it is possible to reduce the range of input parameters again or if time of result obtaining is acceptable, than repeat the experiment by using All combinations algorithm or Hill Climb algorithm, else repeat the experiment by using the Adaptive Thermostatistical SA algorithm.

The authors used this procedure in more solutions. However it is necessary to emphasize that the realization of simulation optimization will always be a compromise between acceptable time and accuracy of found solution.



	Evaluation	ucelova_ funkcia	Polotovar 1 .Inter	Polotovar 2 .Inter	VD1 .Value	VD2 .Value
1	45	198	11	19	3	3
2	52	200	11	21	3	3
3	44	213	11	17	3	3
4	13	364	5	31	1	7
5	35	481	11	15	3	3
6	27	1103	11	11	1	1
7	26	1111	13	11	1	1
8	181	1134	5	61	1	3
9	240	1134	13	65	1	3
10	179	1137	5	63	1	3
11	239	1138	13	63	1	3
12	176	1147	25	61	1	3
13	32	1148	11	33	3	1
14	33	1150	11	35	3	1
15	34	1152	11	15	3	1
16	59	1152	11	21	3	1
17	175	1154	25	61	3	3

Fig. 4 The best results of optimization process.

WITNESS Optimizer presents its reports as the algorithm is running. The main tables and charts can be interacted with during the run to view, sort, copy, paste and analyze. One example of report is outlined in fig.4. The results report on the value of the objective function, parameter settings, tracked function values, variations between replications, confidence intervals and other analyses such as parameter effects. Further analysis of any of the produced tables is available using the direct.

IV. Conclusion

On the basis of experience of authors it is necessary to mention advantages and disadvantages of simulation optimization.

Among the strengths of simulation optimization belong

1) Simple usage for varied problems e.g. optimization of production objectives (costs minimization, flow time minimization, capacity utilization maximization, final production maximization etc.), determination of optimal lot size of production batch.
2) The created simulation model can be more accurately substitute the real system as it mathematical model. The mathematical model of real system usually represents only very simplified approach.
3) Definition of objective function is very simple. The complex mathematical equipment is not needed.
4) Also determination of input variables and their constraints is very simple.
5) Simulation optimization is running automatically.
6) The results are clearly presented.

The opportunities to use simulation optimization successfully in manufacturing system areas seem in performing enterprise-wide analyses of organizations for example for supply chain. The following area is embedding inside of other software support mainly in job shop scheduling. Simulation optimization can be used in real time decisions making.

Weakness of simulation optimization:

1) The simulation model has to be created. There the problems with validation of simulation model can occur
2) The optimization process can run for a long time.
3) There exists risk that global extreme will not be found. Deadlock in local extreme is possible (it is connected with algorithm selection).
4) Result accuracy is impossible always to guarantee.Result can be only near global extreme. It is the compromise between accuracy and time of result gaining.

There still predominates mistrust in simulation optimization results in Slovakia. The managers are not ready to use it in a real way. Also the price of software packages which is too high now, it does not support its broader usage.

There are more areas where simulation optimization would be used. Of course the choice of the procedure used in simulation optimization depends on the analyst and the problem to be solved. The simplicity and good software aid seem as strong assumptions for real using of simulation optimization. The user does not need to be a good mathematician to realize simulation optimization. We believe that the increasing of the efficiency and simplicity of applications of simulation optimization would be valuable.

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